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Kochi, India case study of climate adaptation to floods: Ranking local government investment options

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ABSTRACT

Climate adaptation is uniquely linked to location, making it predominantly a local government and community responsibility. Despite the obligation to act, local governments are hindered by the absence of applicable guides to adaptation decision-making, especially adaptation to extreme events. In this paper, we describe a framework for prioritising adaptation options that could be locally implemented and illustrate it with a study of flooding in Kochi: a city in southern India. Unlike many demand driven, economics based studies, our new framework also incorporates non-economic dimensions of the extremes and potential adaptation options. Local knowledge is used to tackle data gaps and uncertainty related to extreme events: local experts select adaptation options that offer additional benefits besides those related to climate change. These co-benefits aid decision making under uncertainty by giving weight to community priorities. The Indian case study reveals that, risk evaluation and reduction need to be locally contextualised based on resources available, immediate community requirements, planning periods and local expert knowledge. Although there will be residual damage even after implementing selected options, we argue that, climate response will be most likely to be accepted when it also supports pressing needs.

1. Introduction: adaptation options for floods in Kochi Municipal Corporation

The Intergovernmental Panel on Climate Change (IPCC) reports emphasise that anthropogenic climate change will result in an increase in the frequency and severity of extreme events (IPCC, 2007a). Currently available climate projections do not help local level decision makers to select adaptation options because there is little skill at local scales (IPCC, 2007b). Local adaptation is unique and closely linked to the extremes that could result in serious economic, environmental and social damage to the location. Absence of suitable localised future projections results in decision-making being caught between a moral and increasingly legal obligation to be proactive for the future welfare and the requirement for economic rectitude that is hindered by uncertainties about the occurrences and impacts of the future events. In this paper, we suggest a framework that can be applied at local levels to decide on adaptation actions for weather extremes focussing on Kochi Municipal Corporation (KMC) in India.

Indian regions are highly susceptible to climate change and are further threatened by their highly populated coastal area, population growth, rapid but uneven development, monsoonal climate and other future uncertainties. The case study location, KMC is situated in the state of Kerala (South West coast of India). Kerala was decentralised in 1994, empowering the local bodies with responsibility for the majority of schools and hospitals in the local area, planning social welfare, introducing poverty alleviation schemes and arranging basic services like water supply, sanitation, storm water drainage and urban roads. This transfer of power makes the response of local authorities in regard to climate adaptation crucial. Often local councils are left with a portfolio of options to prepare for future climatic changes without proper guidance on decision-making. The framework we showcase here will help councils to choose better adaptation investments.

2. Framework to prioritise adaptation options

We explain the framework for prioritising adaptation options with the help of a block diagram (Fig. 1). In our framework we include the following three major tasks: (1) risk identification; (2) risk evaluation and (3) risk reduction.

2.1. Identifying location specific risks

The climate of Kerala is distinctive as almost 80% of the annual rainfall is received during the South West monsoon (June, July,

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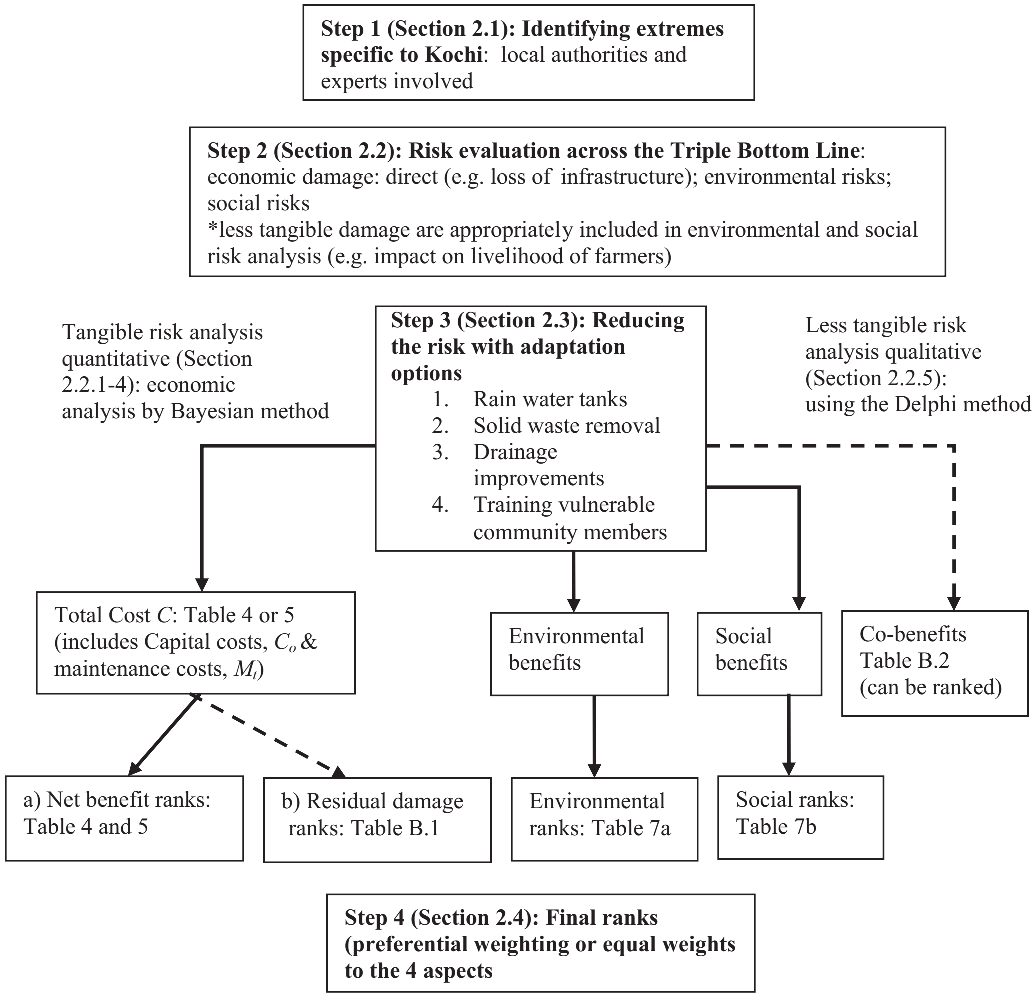

Fig. 1. Block diagram of the framework used for prioritising the adaptation options. Solid lines indicate the path followed for prioritisation in this paper and the broken lines represent other potential criteria that need consideration while prioritising.

August and September) and the rest through the North East monsoon (October and November) (Simon and Mohankumar, 2004). The monsoon and non-monsoon seasons are noted by marked differences in rainfall received as seen in Fig. 2a. The amount of rainfall received varies annually resulting in years of floods and droughts (Krishnakumar et al., 2009). The average daily temperature in KMC varies between 25 and 30 °C, reaching its maximum during the pre-monsoon months (Fig. 2b).

Kerala faces annual floods due to monsoon rains coupled with inadequate drainage systems, flat terrain, unplanned land use, impermeable surfaces, soil texture and high tides (State of the Environment Report, 2007). According to the local experts, floods within KMC are mainly human-induced and can be mitigated to a great extent through proper planning. Experts also suggest that roughly every 20 years, an extreme local flood can be expected in KMC, when the daily rainfall exceeds ~200 mm in 24 h. At present, such floods in Kochi are dealt with on an *ad hoc* basis rather than by appropriate planning for the present and precautionary measures for the future. Here taking KMC floods as an example we describe the prioritisation process depicted in Fig. 1.

2.2. Risk evaluation across the Triple Bottom Line

It will be unrealistic to exclude regular floods from the risk analysis, as their damage accumulates and becomes appreciable over 40 years (time horizon considered). So we consider both regular and extreme floods in our analysis. Firstly, we argue that, though local governments prefer economic justifications behind their adaptation decisions, a complete economic assessment is ethically impossible because of losses like the value of life of people. So in this specific case, we restricted economic risks to infrastructure damage which are comparatively easier to visualise as quantifiable damage. Hereafter, infrastructure damage will be referred to as 'economic damage'. All other damages are categorised into environmental and social risks. Environmental challenges include reducing agricultural losses, maintaining water quality and healthy ecosystems and improving environmental cleanliness. A number of vector borne diseases like malaria, dengue, chikungunya, filariasis, Japanese encephalitis and leishmaniasis also affect the community during floods (Dhiman et al., 2010). These compounded by other economic and environmental damage affect the socio-economically vulnerable communities, particularly in a rapidly developing country, to a great extent. A complete risk assessment will thus need to be done across the Triple Bottom Line (TBL) including all economic, environmental and social damage. First we will discuss evaluation of economic damage of an extreme event.

2.2.1. Economic analysis of the damage due to floods in KMC

In general, the analysis of extreme events is difficult because of the very few observations available. This problem is often further exacerbated by incomplete recording of historical data of the

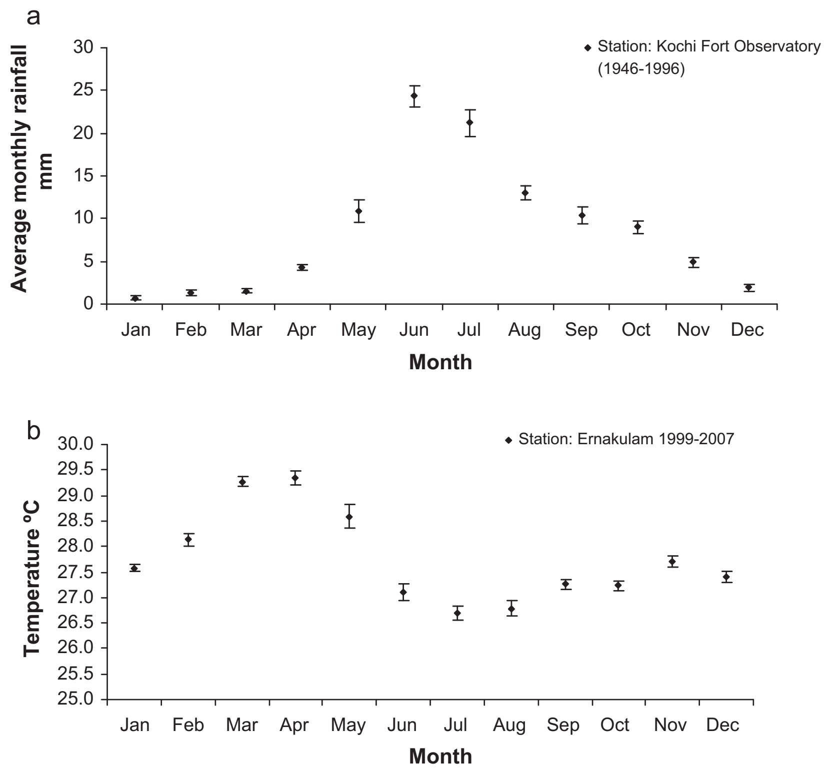

Fig. 2. (a) Average monthly rainfall distribution in mm in Kochi Municipal Corporation. The peak in rainfall during the months May, June, July and August is due to the South West monsoon. The next smaller peak in the rainfall distribution is during October and November: the North East monsoon. Error bars show the standard error of the rainfall data (1946–1996) for the station Kochi. Source data: National Data Centre, India Meteorological Department, Pune, India. (b) Average monthly temperature (°C) variation for Kochi Municipal Corporation. The temperature usually peaks just before the onset of the South West monsoon in April. The station Ernakulam which has very similar climate data as in Kochi Fort observatory (the station used for rainfall data) has been used to depict annual temperature variations as temperature data were available for only this station from the National Data Centre Pune. Error bars show standard error for the temperature data (1999–2007) for station Ernakulam. Source data: National Data Centre, India Meteorological Department, Pune, India.

damages and the scale of study. The limited number of event occurrences restricts us from using the frequentist approach of fitting a distribution on the data and estimating the distribution parameters. Thus, here we use a Bayesian approach of soliciting expert opinions and updating the judgements with available observations (e.g. Gelman et al., 2004; Shevchenko and Wüthrich, 2006; Bühlmann and Gisler, 2005). In this method, both the observations and the parameters of the distributions are considered as being random.

Consider a random vector of observations $\mathbf{X} = (X_1, X_2, \ldots X_n)$ whose density for a given vector of parameters say $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots \theta_n)$ is $f(\mathbf{X}|\boldsymbol{\theta})$. Then the Bayes theorem can be formulated as

$$f(\mathbf{X}, \boldsymbol{\theta}) = f(\mathbf{X}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}) = \hat{\pi}(\boldsymbol{\theta}|\mathbf{X})\, f(\mathbf{X}) \tag{1}$$

where $f(\mathbf{X}, \boldsymbol{\theta})$ is the combined density of the observed data and parameters, $\pi(\boldsymbol{\theta})$ is the density of the parameters (called the prior distribution), $\hat{\pi}(\boldsymbol{\theta}|\mathbf{X})$ is the density of the parameters given the observations $\mathbf{X}$ (called the posterior distribution) and $f(\mathbf{X})$ is the marginal density of $\mathbf{X}$ which can be written as:

$$f(\mathbf{X}) = \int f(\mathbf{X}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})d\boldsymbol{\theta} \tag{2}$$

Note that if $\pi(\boldsymbol{\theta})$ is a discrete distribution the integration should be replaced by a summation.

Let X_{n+1} be a future observation conditional on all available information $\mathbf{X} = (X_1, X_2, \ldots X_n)$ and assume that conditionally, given the parameters $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots \theta_n)$, X_{n+1} and $\mathbf{X}$ are independent. Then the density of X_{n+1} given $\mathbf{X}$ is

$$f(X_{n+1}|\mathbf{X}) = \int f(X_{n+1}|\boldsymbol{\theta}) \times \hat{\pi}(\boldsymbol{\theta}|\mathbf{X})d\boldsymbol{\theta} \tag{3}$$

and the posterior distribution from Eq. (1) becomes

$$\hat{\pi}(\boldsymbol{\theta}|\mathbf{X}) = f(\mathbf{X}|\boldsymbol{\theta})\frac{\pi(\boldsymbol{\theta})}{f(\mathbf{X})} \tag{4}$$

where $f(\mathbf{X})$ is considered as a normalisation constant and hence the posterior distribution becomes the product of a prior distribution with the likelihood of the observed data.

In general, the steps to be followed in the Bayesian method are (for a more detailed description of the chosen approach, see Gelman et al., 2004; Shevchenko and Wüthrich, 2006; Berger, 1985; Shevchenko, 2011):

1. The prior distribution is estimated with the help of expert judgements.
2. The posterior distribution is obtained by updating the prior distribution with the observed data.
3. A predictive distribution of X_{n+1} is calculated using Eq. (3).

Next we apply this method to model the frequency and then the severity (economic damage) of the extremes.

2.2.1.1. Frequency modelling. The frequency of the extreme events being discrete non-negative numbers is modelled using a Poisson distribution. Let $\mathbf{N} = (N_1, \ldots N_n)$ be independent random variables from a Poisson distribution with parameter λ and density

$$f(\mathbf{N}|\lambda) = e^{-\lambda}\frac{\lambda^N}{N!}, \quad \lambda \geq 0 \tag{5}$$

In the first step of the Bayesian process, a prior distribution (gamma distribution) was derived from local experts to obtain an estimate for the parameter λ. The actual event occurrences were then used to obtain the likelihood of the number of data $f(\mathbf{N}|\lambda)$.

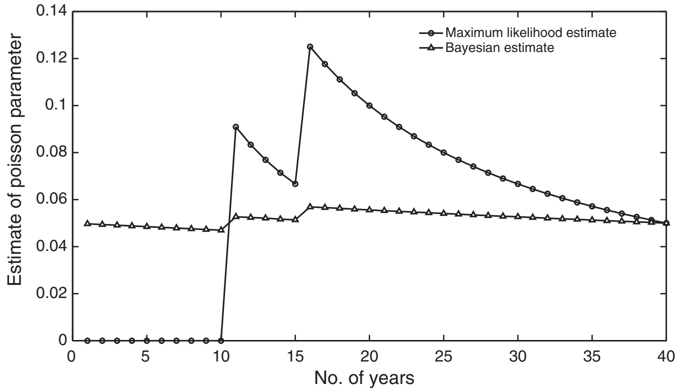

Fig. 3. The Bayesian (triangles) and the standard maximum likelihood estimates (circles) of the observations vs years. The annual observation (occurrence) of the extreme floods for the past 40 years is **X** = [0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0] and the maximum likelihood estimate is a simple average of the observed occurrences of the extreme events.

Secondly, a posterior distribution was derived by combining the prior distribution with the likelihood as given in Eq. (4). Finally, the initial parameter value suggested by experts λ = 0.05 (i.e. extreme floods every 1 in 20 years) was updated using actual observations (Fig. 3) to obtain a posterior distribution that follows a Poisson distribution with parameter $\lambda_E = 0.054$ (calculations in Appendix A). Note that in our approach we assume that for the years where there is no extreme flood, due to the annual monsoon rains in this region, there will still be localised flooding that can be described by the parameters for a 'regular' flood.

The main advantages of using the Bayesian method for extreme events are:

(1) In a case where data are under-reported or unavailable, expert estimates will be very useful.
(2) The time window of the observations taken for analysis is very important for extreme events. For example, consider the case when observations were begun 5 years ago and there was an extreme event within this time window, which was actually a 1 in 100 year event, the analysis would result in overestimating the frequency of extreme events. In the same way, if we consider a time window without any reported events and rely only on data, an underestimation of the results can also eventuate. In Fig 3, if we consider only the first 20 years of observation the Poisson parameter λ will be overestimated as the 2 extreme events fall in this period.
(3) Fewer observations in the modelling process will mean that the posterior distribution will resemble the prior distribution. As more data become available, the posterior distribution will be more refined and will better represent the real situation.

2.2.1.2. Severity modelling. Severity of the events (economic damage) during a flood was modelled using the Lognormal distribution: $LN(\mu,\sigma)$. Given parameters μ and σ, the loss severity X then follows the Lognormal distribution with density function

$$f(x|\mu,\sigma) = \frac{1}{x\sqrt{2\pi\sigma^2}}\exp\left(-\frac{(\ln x-\mu)^2}{2\sigma}\right) \tag{6}$$

while the expected loss is given by

$$E[X|\mu,\sigma] = \exp\left(\mu + \frac{1}{2}\sigma^2\right) \tag{7}$$

In the following, the procedure for deriving the distribution function for both regular and extreme floods will be illustrated. The parameter estimates for severity were derived solely based on the experts' best estimates as given in Table 1, as actual data on damage from flooding was not available at the local scale. Lognormal parameters for regular floods μ_R and σ_R were solved using expert estimates for the 5th and 95th percentiles, while the extreme flood parameters μ_E and σ_E were calculated using Eq. (8), where the average loss of an extreme flood, an interval [a,b] into which the observed loss will fall and a probability p were given by the experts.

Table 1
Expert best estimates on the damage caused by (1) regular flood and (2) extreme flood and the associated lognormal parameters derived from the damage estimates.

Events	Information obtained (MRs) (used for estimating Lognormal parameters)	Lognormal parameters (μ, σ) (approximated to 3 decimal points)
Regular floods	5th percentile = 5.5 95th percentile = 160	17.203, 1.024
Extreme floods only	Average = 175 Range for loss 160–190 with probability 0.25 $Pr[160 \le X \le 190] = 0.25$	18.945, 0.268

$$Pr[a \le X \le b] = p = F^{(LN)}_{\mu,\sigma}[b] - F^{(LN)}_{\mu,\sigma}[a] \tag{8}$$

$F^{(LN)}_{\mu,\sigma}[a]$ and $F^{(LN)}_{\mu,\sigma}[b]$ denote the Lognormal cumulative distribution functions at a and b.

All calculations have been made in (MRs) Millions of Rupees. Rupee is the currency of India. Note that generally it is more reasonable to assume that a distribution modelling extreme events will yield higher values of σ than when 'normal' loss events are modelled. However, as indicated in Table 1 based on the expert opinions we obtain parameter estimates for the Lognormal distribution with $\sigma_E = 0.2677$ being significantly smaller than $\sigma_R = 1.0239$. This is partly because the experts were only able to give information on the average values of the distribution and not on the tails and provided a fairly small range $[a, b] = [160MRs, 190MRs]$ into which the losses from extreme floods would fall, with probability 0.25.

On the other hand the estimated location parameter $\mu_E = 18.9445$ is significantly higher for extreme floods than for regular floods $\mu_r = 17.2033$. The expected values of the loss for regular and extreme floods were obtained as 50MRs and 175MRs respectively. So at least the average damage of an extreme flood will be significantly higher than the loss arising from what is characterized as a regular flood. Overall, the derived distributions, being based on expert opinions, are not in line with theory on modelling extreme events that would suggest a significantly higher volatility for catastrophic losses. However, despite doubts on the validity of the estimates given by the local experts, since no additional information on actual losses from local floods was available, we decided to stick to the derived distributions. It is important to note that in future work on modelling catastrophic losses at the local scale it might be worthwhile to challenge expert judgements when they are not in line with theoretical results on catastrophic risks.

We also point out that severity modelling could also be done using alternative distributions like, e.g. the Generalised Pareto distribution (see Engeland et al., 2004), which helps to model data above a particular threshold. Here, the expert opinions obtained were not sufficient to determine the values of all three parameters of a Generalised Pareto distribution and hence a lognormal distribution was used. Before we discuss the frequency-severity model, it is essential to address one of the main controversial terms of economic analyses, the discount rates.

2.2.2. The discount rate dilemma

Discounting as a procedure involves expressing future and present values of particular variables in a common unit so that decisions regarding possible courses of action in the present can be made rationally. In our analysis, damage from flooding are spread over 40 years which is the time horizon used for the economic calculations. This means the costs and/or benefits should be converted to present value figures for comparisons. To do this, we have to use discount rates to convert monetary measures to a common point in time (2010 *Rs*). There is considerable ambiguity and indeed controversy in the literature concerning the choice of an appropriate discount rate to be used in project evaluation. The basis of this controversy is twofold:

(i) the relationship between discounting in a financial sense and discounting in an economic sense
(ii) in the context of discounting in an economic sense, the magnitude of the discount rate that should be used

In particular for evaluating climate change adaptation or mitigation strategies, there is a wide discussion on what should be used as the appropriate discount rate. While the reports by Stern (2006) and Garnaut (2008) recommend the use of rather low social discount rates, their arguments have been criticized by various authors. Other publications on the issue include, e.g. Nordhaus (2007), Quiggin (2008) and Tol and Yohe (2009) just to mention a few.

Financial discounting involves the comparison of explicit monetary flows – hence discounting is necessary to convert future dollars (expected net earnings) into present dollars so that a valid comparison can be made with known costs that must be incurred in present dollar terms. Clearly it is desirable in a financial context to use a discount rate that reflects the cost of capital (or the cost of acquiring funds) in some way – using a rate lower than the cost of capital associated with the project implies that avoidable losses will be incurred. On the other hand, discounting in the economic sense involves comparisons between future and present *welfare*, and so raises a different set of questions. The paradigmatic case in economics (relevant to the current project) is the choice among available public investment projects, each of which involves the use of resources in the present and the generation thereby of a path of welfare. The optimal adaptation option in an economic sense is the one which maximises welfare. Clearly the comparison of projects necessitates the conversion of future welfare (i.e. the welfare of future agents) into present-welfare equivalents, i.e. discounting. Unlike the financial case, there is no obvious ‘commonsense’ value of the discount rate to use in comparing welfare streams. The choice of discount rate is a choice between the weight given to the interests of agents in the present and near future, and the interests of agents further separated in time from the project's implementation. Intergenerational equity concerns result in a low discount rate as it treats future and present generation's consumption almost equally. A high discount rate is usually a reflection of the market interest rate or rate of return and is drawn from the idea that people prefer to consume today rather than in the future.

Garnaut (2008) suggests a discount rate of 1.35% that is set as the sum of the pure time preference (0.5%) and consumption growth rate (1.3%) up to 2100. Stern (2006) also uses a very low discount rate of approximately 1.4% while Nordhaus (2007) criticized the Stern Review for its use of a low discount rate and suggests a higher discount rate of approximately 3%.

Some advocates of the market interest rate suggest that the interest rates of risk free savings or bonds should be considered for the values of a discount rate (Van den Bergh, 2010). According to Markandya and Halsnaes (2001), discount rates used in assessing climate change programs should at least partly reflect the opportunity costs of capital such that a discount rate of around 4–6% is suggested for developed countries, while in developing countries, a rate of 10–12% is recommended.

In short, the disparity between the choices of an appropriate discount rate emerges mainly from differences in ethical judgements and real interest rates. At a national scale, governments have more liberty in choosing appropriate discount rates but, at local government levels, actions are constrained by fixed budgets and hence the discount rate is primarily driven by the fund allocations. Hence, the discount rates at local government levels mainly depend on:

(1) Funds available
  (a) Assume the cost of options is provided by a non-profit organisation trying to improve the health and well-being of the community. Here, a very low discount rate is expected.
  (b) Further, consider a situation where the fund source is a loan provided by a commercial bank, where the interest rate is current. Here, a discount rate equivalent to the interest rate, say 10%, is appropriate.
(2) Local contexts
  (a) Planning periods, political tenures and interests, community priorities (immediate versus future) and geographic position of the location (developed vs developing; coastal vs mainland).

Initially, a discount rate, $d = 6\%$ was chosen as a reference case. This value was based on the average of the real interest rates for India for the period 1978–2008 (World Bank database[1]). This data varied between -1 and 11%. The discount rate value being uncertain, in our analysis we conduct additional sensitivity tests, using alternative discount rates d = 1%, 3%, 6% and 10%. The choice of the discount rate also decides whether an adaptation option is economically preferable, but later in the paper, we restrict the sensitivity tests only to check whether the ranking of the adaptation options will change with varying discount rates.

2.2.3. Modelling floods in KMC: frequency-severity model

In the following we will provide the procedure that is used to model total losses from regular and extreme floods using the determined distributions for frequency and severity. As mentioned above, in our framework we distinguish between extreme and regular floods. Note that in years with extreme floods, according to the information provided by the experts we assume that the regular floods are replaced by N_t number of extreme events, such that in each year, there will either be a regular flood or N_t extreme floods. Therefore, we start with a general case where the Poisson distribution with parameter $\lambda_E = 0.054$ is used to model the annual number of extreme floods N_t that occurs in year t. In case the simulation of the Poisson random number suggests that there is an extreme flood in year t ($N_t > 0$), then the severity of the flood is simulated using the parameters for extreme floods. In case there is no extreme flood in year $t(N_t = 0)$, we assume that due to the annual monsoon rains in this region, there will still be localised flooding that can be described by the parameters of a ‘regular’ flood. Given the parameter estimate $\lambda_E = 0.054$, in approximately 95% of the years there will be no extreme flood but only a regular flood. Further note that the number of regular floods being based on monsoon rains is limited to one per year. Therefore, the total loss $Z_{T,t}$ in

[1] World development indicator, Real interest rates for India available at http://data.worldbank.org/country/india.

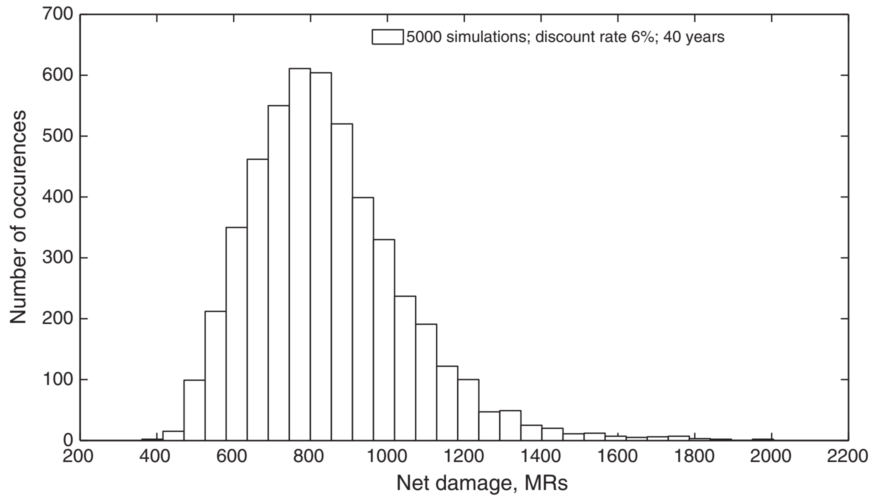

Fig. 4. Damage over 40 years modelled with 5000 simulations and a discount rate of 6%; 95th percentile of the simulations = 1223*MRs*.

year t can be described as

$$Z_{T,t} = Z_{E,t} + Z_{R,t} = \sum_{i}^{N_i} X_i^{(E)} + I_t X^{(R)} \tag{9}$$

where I_t is simply an indicator variable with $I_t = 0$ for $N_t > 0$ and $I_t = 1$ for $N_t = 0$. To calculate the present value of the occurred losses, for each year, $Z_{T,t}$ is then discounted by $(1 + d)^t$ in order to obtain the overall present value of the discounted losses. From Eq. (9) it is clear that expected losses for each year can be calculated analytically based on

$$E(Z_{T,t}) = E(Z_{E,t}) + E(Z_{R,t}) = \lambda_E E(X^{(E)}) + P(N_t = 0) E(X^{(R)}) \tag{10}$$

where $E(X^{(E)})$ and $E(X^{(R)})$ can be derived from the estimated Lognormal distributions for extreme and regular floods with parameters μ_E, σ_E and μ_R, σ_R, respectively. Further, 5000 Monte Carlo simulations were run to determine the 95th percentiles of the loss distributions. Higher quantiles of the loss distribution could have also been derived based on the Panjer recursion formula (Panjer, 1981); however, we decided to use Monte Carlo simulations. The estimated 95th percentiles might also be considered in the decision making process, as they inform local stakeholders about the potential damage under a worst case scenario. A sample simulation is shown in Fig. 4 with d = 6% (base case) to illustrate the distribution of the simulated losses. We consider the expected losses for decision making and the worst-case scenario given by the 95th percentile of the simulated loss distribution only for reporting purpose. Clearly, the net impacts are dependent on the discount rates, but are not high, even after discounting over 40 years as seen in Table 2. It is also pertinent to note that only infrastructure damage for KMC was considered. An advantage of sticking to only infrastructure damage is that local authorities need not wait until all the less tangible entities are converted into monetary units. Moreover, no matter how much time and effort is spent on an economic analysis, there will inevitably be intangibles rendering any conversion only partial. Therefore, in the next section, we also use a qualitative approach to determine other non-economic damage.

2.2.4. Qualitative assessment of environmental and social risks

Flood impacts in KMC are not limited to the monetary losses people often 'see', but include less tangible environmental and social impacts. A way to analyse the social and environmental impacts is by attributing value to them wherever possible (Costanza et al., 1997). These 'market' values are usually under-estimated and, as a result, some serious problems may be overlooked. In any case, a complete conversion of the social and environmental impacts into monetary terms is time-consuming, costly and virtually impossible. In recognition of the disadvantages of using 'dollar values', a qualitative approach of assessment for the non-market impacts has been adopted here. This decision was further justified in view of the fact that this study does not need absolute estimates for the adaptation options; instead, comparative valuation of the options will be sufficient for the prioritisation undertaken.

The Delphi method that is widely employed in organisational improvements, framing curriculum, policy development, etc. (see Kaplan et al., 1950; Wright, 2006; Chu and Hwang, 2008) was used to assess the options. The Delphi method is a structured process of eliciting experts' opinions through a series of rounds. The participating experts have an opportunity to refine their views based on the arguments put by fellow experts and this refinement helps to attain a certain degree of consensus among the experts. So in the initial phase local experts were consulted to gain insight into the potential social and environmental risks of the location. Expert intuition regarding non-climate barriers like population increase and rapid socio-economic developments were also incorporated in the process. After risks have been analysed across the TBL, the benefits of the adaptation options have to be evaluated.

Table 2
Expected damage in *MRs* due to (a) all floods (extreme + regular) and (b) extreme floods with discount rates 1%, 3%, 6% and 10% for 40 years.

Events	(a) All floods (regular + extreme)				(b) Extreme floods			
Discount rate	1%	3%	6%	10%	1%	3%	6%	10%
Average damage (*MRs*)	1866	1313	854	555	310	218	142	92
95th percentile (of simulations) (*MRs*)	2539	1795	1223	829	689	451	344	269

Table 3
Best guesses for reduction in damage by each adaptation option and updated loss (impact) distribution parameters for each adaptation option for regular floods and extreme floods.

Adaptation options	Reduction in damages due to the adaptation options (experts' estimate)	Regular floods: updated lognormal parameters (μ, σ) (approximated to 3 decimal points)	Extreme floods: updated lognormal parameters (μ, σ) (approximated to 3 decimal points)
Rain water harvesting tanks	15%	17.04, 1.024	18.782, 0.268
Municipal solid waste removal	35%	16.77, 1.024	18.514, 0.268
Improving existing drainage and sewerage systems	55%	16.40, 1.024	18.146, 0.268
Training vulnerable community members to emergency response	4%	17.16, 1.024	18.90, 0.268

2.3. Risk reduction using the adaptation options

Adaptation options were chosen in consultation with local authorities. These options were similar to the priorities obtained from a survey conducted by the Asian Development Bank (Kerala Sustainable Urban development Project Report, 2005), except that the experts also suggested 'training of the local residents for emergency situations' as an option. The options were restricted to measures that fall under the responsibility of KMC and were not only in preparation for climate change, but also based on the present immediate needs of the location with an insight into the future possible demands of the community.

The following adaptation options were suggested:

(1) Rain water harvesting tanks for households;
(2) Municipal solid waste removal;
(3) Improvement of existing drainage and sewerage systems; and
(4) Training of vulnerable community members to respond to emergency management.

These adaptation options are highly location specific, being the only options of interest to the authorities in the local area. The choice of options does not affect the framework used to demonstrate the prioritisation. In the next step, benefits of the options are evaluated: we consider economic benefits (cost benefit analysis) as well as social and environmental benefits (Delphi method). Note that also tools like multi-criteria analysis (de Boer et al., 2010) could be used as an alternative to the Delphi method considered in this study.

2.4. Economic benefits

In this section, we investigate the economic benefits of the adaptation options. Expert views on the benefits were obtained. Since we are interested in the net benefits of an adaptation option we also have to consider the monetary costs of implementing and maintaining the adaptation option. To calculate the discounted present value of the implementation and maintenance costs, let t be the time horizon, C_o the initial capital cost of an adaptation option, M_t the annual maintenance cost and d the discount rate. Then the Discounted Present Value (*DPV*) of the costs for an adaptation option can be calculated as

$$\mathrm{DPV} = C_o + \sum_{i=0}^{n} \frac{M_t}{(1+d)^t} \tag{11}$$

The net benefits of an adaptation option are then calculated as the DPV of the reduction in the losses from flooding due to the option (benefits) minus the DPV of the costs of implementing and maintaining the adaptation option (total cost). To quantify the reduction in the risk or potential losses from flooding with respect to the considered adaptation option, again we rely on expert opinions. For example, if the expert suggested a 15% reduction in the net impacts, we assume that the new parameters can be derived by shifting all the information on the mean or quantiles of the distribution provided by the experts by 15% to get the distribution of the reduced impact. Under this approach only the severity parameter μ is changed as the adaptation options are assumed to reduce only the impact of the events and not the frequency. The expert estimates on risk reduction as well as the updated parameters for each adaptation option are provided in Table 3. These values are then used to calculate the benefits from the adaptation options by calculating the DPV of the damage reduction for the expected value and the 95th percentile of the loss distribution.

2.4.1. Sensitivity of the options to varying discount rates

The net benefits (DPV of benefits of the option minus the DPV of investment and maintenance costs) of the considered adaptation options for different choices of the discount rate are summarised in Table 4. A positive net benefit indicates that the option is economically beneficial and a negative net benefit indicates that the option is not economically viable during the period (only with respect to the economic proxy indicator: infrastructure damage). We then examine whether the choice of the discount rate has a significant impact on the ranking of the different options. As indicated in Table 4, the order of the ranks of the adaptation options in this example is not affected by the choice of the discount rate. Only when a discount rate of 10% is considered, the two most preferable options interchange their ranks, because present values of discounted costs and benefits are highly dependent on the chosen discount rate and time horizon. On the other hand when the net benefits are calculated with respect to the tail of the loss distribution (Table 5), the ranks differ considerably from the ranks obtained when the net benefits are calculated with respect to the average economic damage as in Table 4. Still the option 'rain water harvesting tanks' is the economically preferred option in both cases. Note that in the subsequent analysis only the results with respect to the average damage will be used. Hereby, we follow the usual procedure of cost–benefit analysis when different projects are being compared with respect to their net benefits. However, we point out that future work should also focus on the robustness of results with respect to considering average costs and benefits only or net benefits of adaptation options under tail-based risk measures.

Fig. 5 provides a plot of the net benefits of the examined adaptation options with respect to the considered time horizon up to a maximum time period of 40 years. Such an analysis can also determine the time period at which an adaptation option starts becoming beneficial, which is particularly important for KMC as it pursues short term planning for most investments.

As illustrated in Fig. 5, most adaptation options provide negative net benefits in the short term due to the initial investment, which gradually become positive over the years for some of the options. Residual damage and costs of adaptation are also important in determining potential options (see Table B.1).

Table 4
Ranks of the adaptation options for all floods (extremes + regular) based on net economic benefits over 40 years with varying discount rates: 1%, 3%, 6% and 10%.

Adaptation options	*d*	Total Cost in *MRs* (Capital cost + total discounted maintenance cost)	Benefit (*MRs*)	Net benefit (*MRs*)	Rank
Rain water harvesting tanks	1%	149.9 (35 + 114.9)	279.8	129.9	1
	3%	115.9 (35 + 80.9)	197.1	81.2	1
	6%	87.7 (35 + 52.7)	128.2	40.5	1
	10%	69.2 (35 + 34.2)	83.8	14.6	2
Municipal solid waste removal	1%	740.3 (100 + 640.3)	656	−84.3	3
	3%	550.7 (100 + 450.7)	462	−88.7	3
	6%	393.4 (100 + 293.4)	300.6	−92.8	3
	10%	290.7 (100 + 190.7)	195.4	−95.3	3
Improving existing drainage and sewerage systems	1%	1137.5 (152.5 + 985)	1029.2	−108.3	4
	3%	845.9 (152.5 + 693.4)	724.5	−121.4	4
	6%	603.9 (152.5 + 451.4)	471.6	−132.3	4
	10%	445.9 (152.5 + 293.4)	306.5	−139.4	4
Training vulnerable community members to respond to emergency management	1%	2.1 (0.5 + 1.6)	78.8	76.7	2
	3%	1.7 (0.5 + 1.2)	55.6	53.9	2
	6%	1.3 (0.5 + 0.8)	36.1	34.8	2
	10%	0.98 (0.5 + 0.48)	23.5	22.5	1

The options 'municipal solid waste removal' and 'improving drainage and sewerage systems' have smaller residual damages, though they are not economically viable over the period. If the focus is only on risk reduction, with costs not a matter of concern, then ranks can be based on residual damages, but local authorities are usually more concerned about the costs of the options and the net benefits. In the next section, we investigate the impact of climate change on extreme events by changing the frequency and severity of the flood events.

2.4.2. Sensitivity to future climate scenarios

Extreme floods currently occur about once every 20 years (in the present climate). With anthropogenic climate change, the frequency and severity of floods are likely to change with most commentators predicting both more frequent and more severe floods (IPCC, 2007b). Model simulations from PRECIS (Providing Regional Climates for Impacts Studies) developed by the Hadley Centre for Climate Prediction and Research for the Indian region indicate an increase in rainfall varying between 20 and 40% from the baseline period (1961–1990) to the end of the 21st century (Kumar et al., 2006). Climate change induced flood impacts are uncertain at local scales. Local experts suggested an increase in the frequency of extremes and severity of the extreme and regular floods. Thus sensitivity tests with varying frequency and severity were conducted to study their impact. A 6% base discount rate was used in all the sensitivity tests. The frequency of the extreme events was changed from 1 in 20 years to 1 in 10 years and 1 in 15 years while the severity increased by 5%, 10% and 20% for both extreme and regular floods.

The modelled results are substantially higher than the values obtained under the present climate scenario (Table 6) and hence, when we calculate the net benefits (benefits–costs), the adaptation options are more beneficial, although the order of ranks does not change in this specific example. Next, social and environmental net benefit ranks should also be obtained to get the final order of the adaptation options.

2.4.3. Delphi method to analyse the social and environmental benefits

A three round Delphi process was carried out for ranking the social and environmental net benefits. Experts were selected based

Table 5
Ranks of the adaptation options for all floods (extremes + regular) with respect to the worst case damages (95th percentiles of the simulations) over 40 years with 5000 simulations and varying discount rates: 1%, 3%, 6% and 10%.

Adaptation options	*d*	Total Cost in *MRs* (Capital cost + total discounted maintenance cost)	Benefit (*MRs*)	Net benefit (*MRs*)	Rank
Rain water harvesting tanks	1%	149.9 (35 + 114.9)	388.3	238.4	2
	3%	115.9 (35 + 80.9)	266.2	150.3	2
	6%	87.7 (35 + 52.7)	188.4	100.7	1
	10%	69.2 (35 + 34.2)	123.6	54.4	1
Municipal solid waste removal	1%	740.3 (100 + 640.3)	890.8	150.5	3
	3%	550.7 (100 + 450.7)	633.7	83	3
	6%	393.4 (100 + 293.4)	434.8	41.4	4
	10%	290.7 (100 + 190.7)	290.17	-0.5	4
Improving existing drainage and sewerage systems	1%	1137.5 (152.5 + 985)	1409.5	272.0	1
	3%	845.9 (152.5 + 693.4)	998	152.1	1
	6%	603.9 (152.5 + 451.4)	672.6	68.7	2
	10%	445.9 (152.5 + 293.4)	458.6	12.7	3
Training vulnerable community members to respond to emergency management	1%	2.1 (0.5 + 1.6)	119	116.9	4
	3%	1.7 (0.5 + 1.2)	79.6	77.9	4
	6%	1.3 (0.5 + 0.8)	51	49.7	3
	10%	0.98 (0.5 + 0.48)	33.8	32.8	2

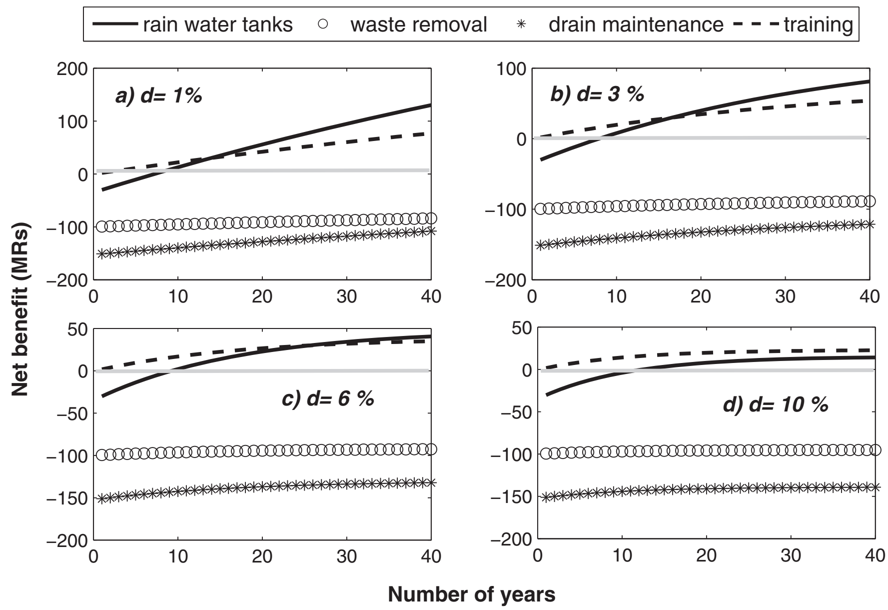

Fig. 5. Annual variation of the net benefits of the adaptation options over the 40 years with discount rates (a) 1%, (b) 3%, (c) 6% and (d) 10%.

on their experiences in social and environmental research projects in Kochi. The number of experts was limited to three, to better understand differences in opinions and make discussions more productive. Usually in a Delphi study, responses of the experts are collected electronically, but in this case, direct contact between the facilitator and the experts seemed to be more convenient and more likely to encourage discussion. Thus the facilitator communicated the arguments put forward by fellow experts after each round and obtained the reviewed ranks. The ranks following the third (last) round were replaced by corresponding Borda votes. If there are N options, then the option ranked '1' gets $N-1$ Borda votes, '2' gets $N-2$ Borda votes and so on (e.g. Saari, 2006; Vainikainen et al., 2008). The Borda votes of all three experts were added and finally the options were ranked in the order of total votes acquired. The same process was repeated for obtaining the ranks for environmental benefits (environmental ranks) as well as ranks for social benefits (social ranks) as detailed in Tables 7a and 7b.

All three experts held a consistent view on the environmental ranks. On the other hand, social ranks differed for two options: 'solid waste removal' and 'improving drainage and sewerage systems'. Experts I and III argued that solid wastes were responsible for blocked drains and resulted in localised flooding or water logging. This in turn, would cause outbreak of many life threatening diseases. Contrarily, Expert II had the opinion that, even if residential waste was disposed properly and regularly, drains will be blocked by large amounts of leaf litter during heavy rains. Thus improving the drainage and sewerage systems was more important. Interestingly, the option 'training vulnerable community members' was ranked last as it contributed least to flood mitigation. Lastly, the experts suggested that, the training option which utilises human capital is important for Kochi and hence it could be combined with other options.

Table 6
Sensitivity of damages (in *MRs*) to varying frequency (1 in 10 year and 1 in 15 year events) and severity (5%, 10%, and 20%) with base discount rate 6% calculated over 40 years.

Frequency	Severity	Average damage *MRs*	95th percentile (of simulations) *MRs*
1 in 15 years	Unchanged	877.7	1244.4
1 in 10 years	Unchanged	940.4	1319.7
Unchanged	5%	897.7	1545.7
Unchanged	10%	940.5	1635.7
Unchanged	20%	1026	1690.2
1 in 15 years	5%	921.6	1582.7
1 in 10 years	5%	987.4	1648.9
1 in 15 years	10%	965.5	1670.7
1 in 10 years	10%	1034.4	1719.4
1 in 15 years	20%	1053.1	1779.3
1 in 10 years	20%	1128.5	1867.3

3. Combining the three aspects of the Triple Bottom Line

In the final stage, ranks across the TBL have to be combined. Preferential weighting could be applied. The weights could depend on the location specific preferences/values followed. Thus the relative importance of social, economic and environmental benefits differs from place to place and can be represented by differential weighting if desired. In Table 8, equal weights are assigned to the economic, social and environmental criteria to demonstrate a simple objective way of combining the ranks. Note that in the actual decision making process, different weights as determined by the authorities are to be used. Borda votes were used to combine the ranks across the TBL.

The option 'municipal solid waste removal' received highest Borda votes (Table 8) and hence was ranked first in the list, but was not economically viable over the time period considered. The option did, however, yield a positive net benefit when the risk reduction in the tail, i.e. the 95th percentile of the losses was considered (see Table 5). This example clearly reveals the danger of decision-making based on economic benefits only, as important social and environmental benefits might be overlooked, just because their monetary value cannot be quantified. If the decision was driven only by economics (discounted net benefits) then 'municipal solid waste removal' would not have been the top preference.

As mentioned earlier, the whole ranking process was based on the average damages. A disadvantage of limiting decisions to averages is that the risks will be underestimated and hence the chosen options may not be sufficient for worst cases. Decision making under worst cases is highly challenging as these values are more sensitive to the assumptions made during the risk analysis

Table 7a
Ranks given by the 3 environmental experts' (I, II and III) combined to get the final environmental benefit ranks using Borda votes.

Adaptation options	Experts' (I, II, III) environmental net benefit ranks			Total Borda votes	Final ranks
	I	II	III		
Rain water harvesting tanks	3	3	3	3	3
Municipal solid waste removal	2	2	2	6	2
Improving existing drainage and sewerage systems	1	1	1	9	1
Training vulnerable community members to respond to emergency management	4	4	4	0	4

Table 7b
Ranks given by the three social experts (I, II and III) combined to get the final social benefit ranks using Borda votes.

Adaptation options	Experts' (I, II, III) social net benefit ranks			Total Borda votes	Final rank
	I	II	III		
Rain water harvesting tanks	3	3	3	3	3
Municipal solid waste removal	1	2	1	8	1
Improving existing drainage and sewerage systems	2	1	2	7	2
Training vulnerable community members to emergency response	4	4	4	0	4

Table 8
Economic (6% discount rate), environmental and social ranks combined using Borda votes.

Adaptation options	Economic ranks, $d = 6\%$	Env. rank	Social rank	Borda votes	Rank
Rain water harvesting tanks	1	3	3	5	3
Municipal solid waste removal	3	2	1	6	1
Improving existing drainage & sewerage systems	4	1	2	5	2
Training vulnerable community members for emergency response	2	4	4	2	4

than the average values. For instance, the same information provided by the experts could be modelled with other fat tailed distributions such as the Weibull or Pareto distribution and the values at the tails could be very different. Conducting sensitivity tests and revisiting experts will be one way to take decisions under such uncertain conditions. Adaptation options that are robust under a wide range of scenarios can also be selected (e.g. Dessai and Hulme, 2007). This method may not be as relevant for a local government as their choice of options are sometimes less flexible due to local constraints including available funding and community needs.

4. Conclusion: adapting to climate change with locally available knowledge

Local governments hindered by predictive uncertainties can and should adopt options with co-benefits. Here we describe a new framework designed to streamline and strengthen local government prioritisation and thus ensure that uncertainty about the future need not curtail precautionary measures. We recommend that local governments choose soft, short term and/or reversible options or also options with additional benefits (de Bruin et al., 2009; Hallegatte, 2009). The options in our case study area have benefits other than directly related to floods (Table B.2) and hence 'co-benefits' can be another criteria to rank the options as seen in Fig. 1. The inclusion of additional benefits results in 'no regrets' decisions, as the society is always better off with the adaptation option in place despite the uncertainty in the occurrence of the events and the impacts of climate change.

In Kochi city, while 'municipal solid waste removal' is the preferred option after completing the prioritisation across the TBL, despite its top position, the net economic benefit of the option is negative. The residual economic damage associated with this option is small and it is economically viable with respect to the worst-case scenario (e.g. net benefit is 42*MRs* with $d = 6\%$) Another positive aspect of this option is that it has benefits even during the non-monsoon seasons. Options that ranked second in Kochi were 'rain water harvesting tanks' and 'maintenance of drainage systems'. The option 'rain water harvesting tanks' is economically viable and also has environmental and social benefits. If the local authority is concerned about achieving a positive net benefit then the option 'rain water harvesting tanks' could be adopted.

This case study shows that even local governments in developing countries working with complex development issues and short term planning times, need not delay adaptation action because of the uncertainty about the exact nature of the future climate, nor because of incomplete information. Investments need not be made solely in preparation for future climate change, but can include adaptations to fulfil the present demands of the community (Tryhorn and Degaetano, 2011). This is particularly attractive if it is synergistic with reducing future climate change-induced impacts. The novel framework described and illustrated here can be applied in locations where local authorities need to manage demands in addition to climate change. As uncertainty always exists and may remain irreducible long into the future, it is reasonable to use practical values for the uncertain parameters. Uncertainty in the parameter space should not be an excuse for authorities failing to take precautionary measures for the welfare of the community as local expertise could help in deciding on suitable adaptation options.

The main objective of our new framework is to encourage local authorities to decide on adaptation measures despite the

challenges faced by the uncertain future impacts of climate change. This Kochi case study shows that climate adaptation measures in a rapidly developing country can deliver community benefits immediately as well as reducing future impacts of extreme climate events. This framework could valuably be applied to other locations where adaptation benefits beyond solely monetary outcomes are deemed desirable.

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Appendix A

Bayesian steps for frequency modelling using Poisson Gamma distribution (see Shevchenko and Wüthrich, 2006 for detailed equations)

Step 1. Prior Gamma distribution

Let the prior distribution be given by *Gamma*($\boldsymbol{\alpha}$, $\boldsymbol{\beta}$) with parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. In most cases, experts prefer to give an intelligent guess of the estimate as lying within an interval [*a*, *b*] with the probability $Pr[a \leq \lambda \leq b] = p$. The values of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ can then be calculated using Eq. (A.1)

$$Pr[a \leq \lambda \leq b] = p = F^{(G)}_{\alpha,\beta}[b] - F^{(G)}_{\alpha,\beta}[a] \tag{A.1}$$

where $F^{(G)}_{\alpha,\beta}[b]$ and $F^{(G)}_{\alpha,\beta}[a]$ are the cumulative Gamma distributions at *b* and *a* respectively.

Here the value of $p = 0.66; b = 1/15; a = 1/30$

The value of $\boldsymbol{\lambda}$ using the prior distribution is given by

$$\lambda_o = \alpha \times \beta, \quad \lambda_o \text{ is calculated to be } 1/20 \tag{A.2}$$

Step 2a. Likelihood of $\boldsymbol{\lambda}$

The likelihood of $\boldsymbol{\lambda}$ given by $f(\mathbf{X}|\lambda)$ is

$$f(\mathbf{X}|\lambda) = \prod_{i=1}^{n} \exp(-\lambda)\frac{\lambda^{X_i}}{X_i!} \tag{A.3}$$

The observations in this case are given by **X** = [0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]

Step 2b, posterior Gamma distribution

The posterior distribution is again a Gamma distribution, $Gamma(\hat{\alpha}, \hat{\beta})$ with updated parameters $\hat{\alpha}$ and $\hat{\beta}$ given by

$$\alpha \to \hat{\alpha} = \alpha + \sum_{i=1}^{n} X_i \quad \text{and} \quad \beta \to \hat{\beta} = \frac{\beta}{(1 + \beta \times n)} \tag{A.4}$$

The values obtained for $\hat{\alpha}$ and $\hat{\beta}$ are 9.885 and 0.0051 respectively

Step 3. Predictive distribution

The updated Poisson parameter ($\hat{\lambda} = 0.0504$) value is now determined from the updated parameters of the Gamma distribution, written as,

$$\hat{\lambda} = \hat{\alpha} \times \hat{\beta} \tag{A.5}$$

After the *k*th year, $Gamma(\hat{\alpha}, \hat{\beta})$, the predictive distribution could be obtained using the updated parameters as indicated below,

$$\hat{\alpha}_k = \hat{\alpha}_{k-1} + X_k \quad \text{and} \quad \hat{\beta}_k = \frac{\hat{\beta}_{k-1}}{1 + \hat{\beta}_{k-1}} \tag{A.6}$$

Appendix B. Criteria (other than TBL benefits) that determine final decision: residual damage and co-benefit of the adaptation options

See Tables B.1 and B.2.

Table B.1
Options ranked in order of least residual damage for all floods with different discount rates.

Adaptation options	Residual damage (*MRs*) (damage-benefit) floods				Ranks
	d = 1%	*d* = 3%	*d* = 6%	*d* = 10%	
Rain water harvesting tank	1585.95	1116.5	726.8	471.9	3
Municipal solid waste removal	1209.7	851.6	554.3	360.3	2
Improving drainage and sewerage systems	836.56	588.9	383.3	249.15	1
Training vulnerable community members for emergency response	1786.92	1257.2	818.8	532.1	4

Table B.2
Co-benefits of the adaptation options.

Adaptation options	Co-benefits
Rain water harvesting tanks	It can serve as an adaptation option for drought periods
Municipal solid waste removal	It is a measure that reduces spread of diseases in the rainy and non-rainy seasons and improves environmental quality in all seasons
Improving existing drainage and sewerage systems	Applicable to all seasons as it reduces to some extent spread of diseases and helps in the environment quality during the regular floods
Training vulnerable community members for emergency response	Social capital is very important during any extreme event and will help during any extreme event

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